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IMPROVING THE PERFORMANCE OF BASIC PROCESS CONTROL SYSTEM FOR OPTIMAL CEILING BOARD PRODUCTION

[1]Odo Nathaniel S., [2]Eneh Innocent I., [3]Ene Princewill C.
[1,2,3] Department of Electrical and Electronics Engineering, Enugu State University of Science and Technology, Enugu, Nigeria
Corresponding Author Email: [1]Odohnath312@gmail.com

Abstract

This paper "improving the performance of basic process control system for optimal ceiling board production" was presented for the intelligent control of dynamic process. The study utilized Feed Forward Neural Network (FFNN), trained with the data of the ceiling board plant collected at ±3% (200 liters) of fluid stability point and used for the adaptation of Programmable Logic Controller (PLC). The FFNN was trained with back-propagation algorithm and evaluated using Mean Square Error (MSE) and Regression (R). The MSE performance after training was $3.8417e^{-10}$, while the R was 0.97173. The FFNN was integrated on the PLC and used for the control of the ceiling board plant, using simulation methodology. The result showed that the chemical fluid stability was maintained at tolerance of ±3% (200 liters).

Keywords: Programmable Logic Controller; Feed-Forward Neural Network; Ceiling Board

1. INTRODUCTION

Production is the creation of goods and services for satisfaction of human wants. This concept can be dated back to the early men, who employed mechanized tools for the production of goods especially in the agricultural sector. This early idea of mechanized tool for production, extended to other manufacturing application and with time in the mid 70's more complex mechanical systems, powered with steam was developed and used for the optimization of manufacturing process. This era was tagged the first industrial revolution (Anthony, 2018).

According to (Mallikarjun, 2017), industrial automation is the process of operating industrial machineries and other related equipment with digital logic control devices and reduction of human intervention via manual command process and decision making. This process has recorded great success in the industrial sector such as maximizing production, reducing the cost of labour, reducing risk reduction factor of technical process.

Most recently in this era of forth industrial revolution, each of these industrial automation layers has gained lots of research attentions. Various methodologies, techniques, laws and algorithms have been proposed, presented and implemented to improved automation process in the three layers (Tan et al, 2015). Such includes the application of internet of things for remote monitoring, more control system designs, modernized process designs, safety instrument systems, redundancy control systems, modernized reactor plant designs, design standards and administrative regulatory bodies (Tan et al., 2015)

Process control employ programmable logic controller to control heavy industrial machineries like actuators, process plants, reactors among other. Because these machineries all exhibit certain levels of nonlinearity during technical processes, control systems are used to ensure stability. These control systems are logic solvers of various varieties, ranging from linear to non linear controller. In simple terms linear controllers are specially designed for the control of linear system-based on superposition theory, while nonlinear controller are set of controllers governed by nonlinear differential equations (Mallikarjun et al., 2017). These two categories of control systems are composed of lots of controllers, but the most used are the PLC and proportional integral differentiator (PID).

According to (Inyama and Azubuike, 2015), these two control systems have dominated the process lines for some decades now with over 95% worldwide industrial applications. However, the problem is that they suffer certain constrains such as delay rising and settling time, aggressiveness, overshoot, which in turn results to poor response and overall control performance in process stability. Therefore, there is need for an improved controller which optimizes the control performance of process plants during nonlinear condition. This will be achieved in this paper using neural network adaptive controller.

Over time researchers presented various studies on the stability of process control system and optimization have been presented which include (Smith, 2017; Parrish et al., 2017; Tan et al., 2015; Telegam, 2016; Tsogas et al., 2018; Rahul et al. 2020), however, despite their success, the work still leaves room for improvement which will be addressed in this paper.

The neural network is a branch of artificial intelligence inspired via human brain and reasoning process. The neural network algorithm will be used to design an adaptive controller using dataset of plant reactor to improve the system. The reference model of the plant will be used to predict and adjust nonlinearity in real time.

2. MATERIALS AND METHODS

This section presents the materials that are required for the development of the system and the method that will be effective for optimization of ceiling board manufacturing process.

2.1 Materials

- Siemens Programmable Logic Controller
- Simatic manager software
- Studio500 software for PLC programming
- Three phase induction motor
- Continuous stir tank reactor tank
- Laptop
- Ultrasonic Sensors
- Contactors
- Power supply
- Human machine interface, etc

2.2 Design Method

The methods used for the system The methodology is the qualitative approach which used the data collected from the technical process at $\pm$3% (200 liters) o ceiling board flow to train a neural network algorithm and generate a prediction model which was used for the optimization of PLC. The three phase induction motor was used for the pumping of the fluid to the plant, while the ultrasonic sensors monitor the stability level and send signal to the controller during tank overflow for control measured using the contactor. The laptop, installed with the Simantic manager software and interfaced with the HDMI was used to monitor the behavior of the process and collect data for analysis.

2.3 Requirements

The requirements for this work are based on the system requirements which ensued that the performance of the industrial technical process satisfied the IEC 61131 standards which guided the programming and modeling of basic process control system, and the IEC 7007-2021 standard which is the latest standard for software based intelligent industrial automation process. These respective standards ensure the process design; basic process control system and operation satisfied the requirements for optimal industrial automation process. The user requirements on the other hand ensure that the basic process control system performs at optimal level to maintain stability in the level with tolerance of $\pm$3% (200liters) of slurry (mixture of cement, silica and cellulose) in the tank at all time, irrespective of the impact of nonlinear constraints.

3. SYSTEM MODELLING

To develop the model of the optimized PLC using machine learning technique, first data was collected from the technical process. The data collected considered the tolerance of $\pm$ 3% (200 litters) and concentration of the tank behaviour. The table 1 presented the attributes of the data collected.

Table 1: Attributes of the slurry characteristics (Mechelle and Haeng-Kon, 2017)

Inputs (S/N)	Parameters	Concentration
1	pH	8.40
2	Total Solid	48000mg/l

3	Water (%)	95.3%
4	Solid content	4.7%
5	Density	2.76g/cm3
6	Hardness	541.1mg/l
7	Sulfates	85.1mg/l
8	Alkalinity	450.1mg/l

These data were used to train a neural network algorithm which was then embedded into the PLC for optimization and Neuro-PLC system. The reason neural network was used ahead of other machine learning algorithms was due to its ability to precisely approximate nonlinearity in fitting problems and maintain steady state (Inyama and Agbaraji, 2015; Eneh and Ene, 2020). The neural network type used is the Feed Forward Neural Network (FFNN) model adopted from (Mba and Asogwa, 2022) and was trained with the data of the tank collected to generate the algorithm used for the optimization of the PLC.

3.1 Mathematical Model of the plant

This figure shows a configuration of a single reactor tank system.

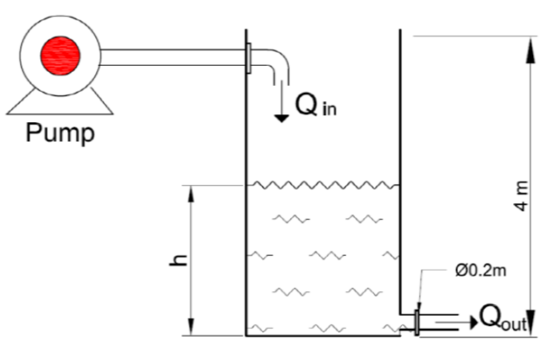

Figure 1: A single Reactor Tank System

The differential equation of the dynamic behavior of the system are proposed as follow:

$Q_I - Q_o$ (the slurry exchange rate in the tank

$$Q_I - Q_o = \frac{dv1}{dt} = A\frac{dH}{dt} = AH: \quad (1)$$

Where Q_i = Pump flow

Q_o = Output flow from the tank

The slurry exchange rate in the tank relates to the slurry volume in the tank (V_1) with time (t) and also can relate to the tank area (A) with height (H) and time (t).

$$Q_o = (C_{db}) \text{ x } (a_b) \text{ x } \sqrt{(2xgxH)} \quad (2)$$

C_{db} = discharge coefficient of the tank; a_b = area of the discharge orifice section.

Replacing equation (2) into equation (1) we will obtain equation (3)

$$Q_I = A\frac{dH}{dt} + ((C_{db})\text{x}(a_b) \text{ x } \sqrt{(2xgxH)}) \quad (3)$$

The equation (3) obtained is a nonlinear first-order differential equation, so, improving the linearity of the slurry level variations in the tank becomes a necessity

3.2 Model of the Neuro- Optimized PLC based control system

The study improved the model of a PLC used at the characterized system which operated based on data collected by the ultrasonic sensor from the set points variation of fluid level and used for the control of the VFD. The model of the PLC was presented in the figure 2 which showed how the information collected from the sensor which represents the tank behaviour was used to execute instructions and command output which controls the rate of slurry flow into the tank via the VFD intelligent control.

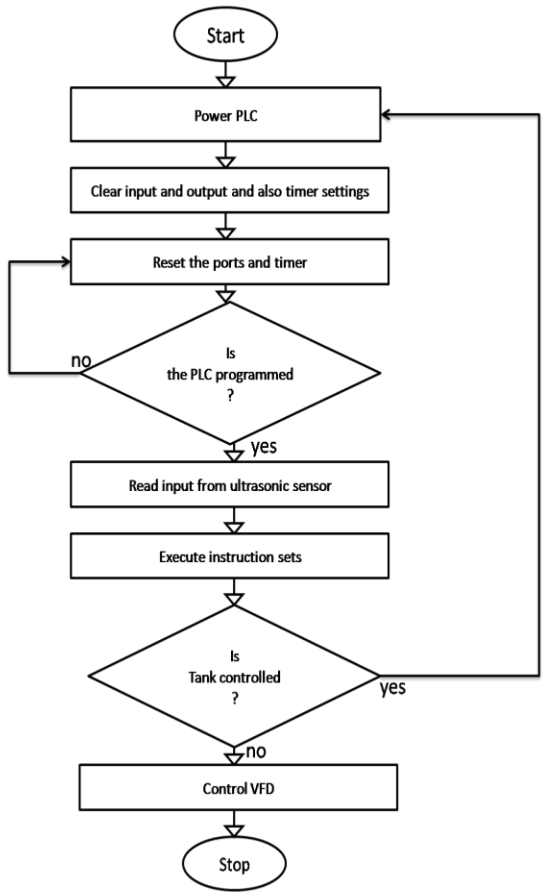

Figure 2: Flowchart of PLC

The flow chart in figure 2 shows the operation of the PLC which was configured with the desired tolerance of the fluid level and then used to control the tank. The sensor monitors the tank and then sends feedback of the tank behaviour to the PLC which then controls the VFD to stability the tank. The challenges encountered as identified in the analysis of the characterized PLC is the issues of delay response time, which results to overshoot of the fluid and in most cases if not controller led to tank over flow and hazard. To address these problems, the FFNN optimization algorithm was used to configure the PLC as a reference knowledge base for control of the VFD. The model of the Neuro- PLC was presented in figure 3;

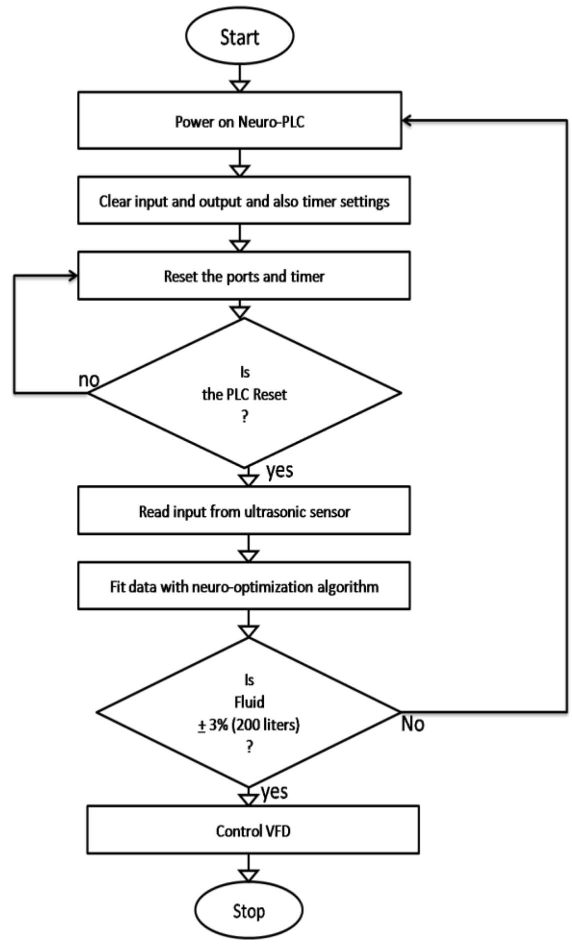

Figure 3: Flow chart of the Neuro-PLC

The figure 3 presented the work flow of the neuro PLC which showed how the PLC used the neural network-based optimization algorithm developed for the stability of the reactor tank. When the sensor sends data to the PLC as input, it used the Neuro-optimizer as reference point to solve the fitting problem and then control the tank. The high-level model of the Basic Process Control System (BPCS) with Neuro-PLC was presented in figure 4 while the specification of the PLC and the neural network was presented in the table 2;

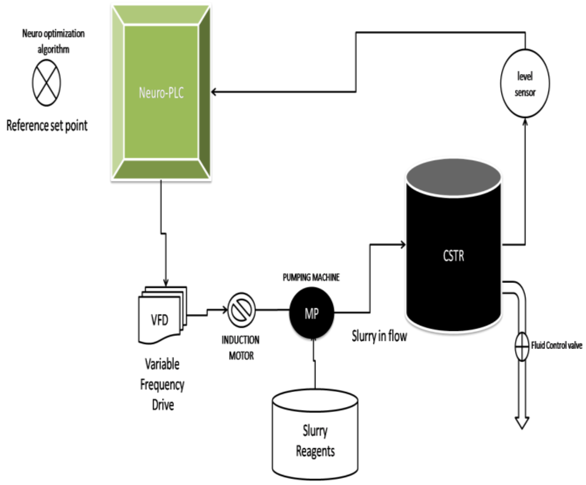

Figure 4: High level model of the Neuro-PLC integrated on the BPCS

Table 2: Specifications of the Neuro-PLC

Parameters	**Values**	**Parameters**	**Values**
PLC type	Siemens CPU224 XP-DC/DC/DC	Input port	8.1
Program memory on load	12288 bytes	Output port	6.1
Program memory off load	16385 bytes	Communication Interface	RS485
Data size	10240 bytes	Power supply	20-24V/DC
Backup memory size	8hrs	Analogue adjustment	2.0
Speed of computation process	3 at 201MHz	Floating point	True

3.3 Model of the Induction Motor

The model of the induction motor is designed considering the relationship between the rotor and stator characteristic in equation 4; The Rotor slip (S) is defined in terms of rotational speed ωm, the number of pole pairs p, and the electrical supply frequency ω. Thus, related by the structure (Eneh and Ene, 2020);

$$S = 1 - p\,\omega_m/\,\omega \qquad (4)$$

For a 3-phase induction motor the torque-speed relationship is given by:

$$T = \frac{npR2}{s\omega}\frac{Vrms^2}{\left(R1+R2+\frac{1-S}{S}R2\right)^{\wedge}2\ +(X1+X2)^{\wedge}2} \qquad (5)$$

Where: V_{rms} is the line-neutral supply voltage for a star-configuration induction motor, and the line-to-line voltage for a delta-configuration induction motor, n is the number of phases which is 3; R_1 is the stator resistance; R_2 is the rotor resistance with respect to the stator; L_1 is the stator inductance; L_2 is the rotor inductance with respect to the stator; L_m is magnetizing inductance; V and I are the sinusoidal supply voltage and current phasor. In a case where torque is known, and the speed of the motor determined, power is defined as (Eneh and Ene, 2020);

$$P\ (KW) = \frac{Torque * speed}{9.5488} \qquad (6)$$

4. SYSTEM IMPLEMENTATION

The system was implemented using simulation method. The simulation was done after Simulink was used to implement the models developed using neural network toolbox, control system toolbox and optimization toolbox. The models were used to configure the toolbox and then implement the basic process control system. The Simulink of the Neuro-PLC was presented in figure 5, while Simulink of the interconnected Neuro-PLC to the tank was presented in figure 6;

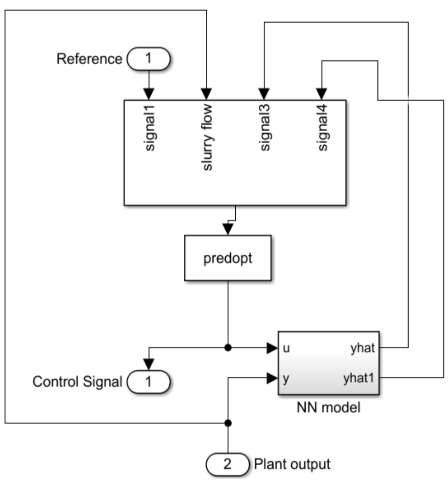

Figure 5: The Neuro-PLC model

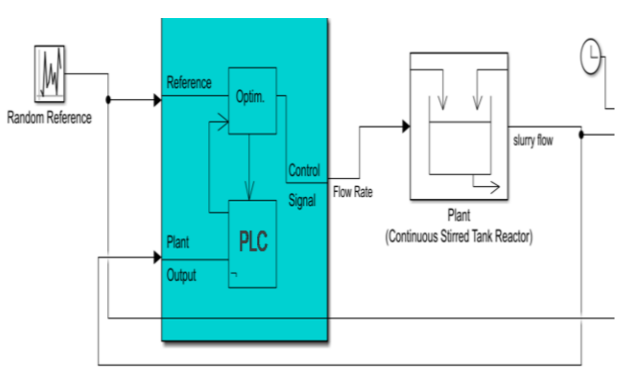

Figure 6: Simulink model of the basic process control system with Neuro-PLC

The model in figure 6 is the Simulink of the BPCS with the Neuro-PLC. The model of the technical process which showed how the Neuro-PLC was connected to the VFD which controls the motor and hence the pumping machine was presented in the figure 7;

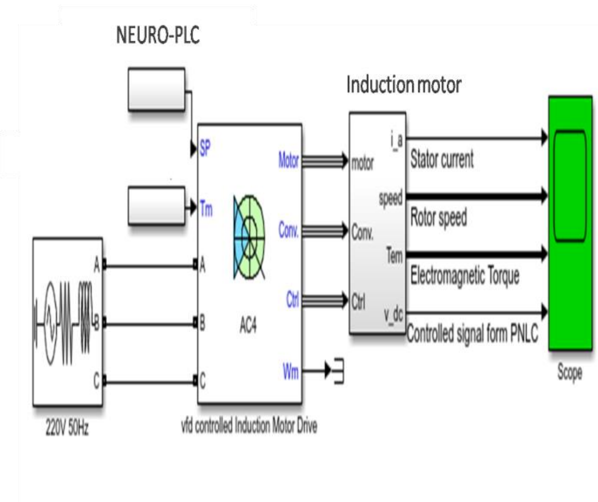

Figure 7: Simulink of the technical process.

5. RESULTS AND DISCUSSION

This section presented the results of the Neuro-algorithm during the training process. The aim here was to evaluate the performance of the neurons during the training process and test the capacity in reading instability on the tank. To achieve this, the MSE was used which is a tool to measure the error which occurred during the training process and ensure that it is acceptable. The result of the MSE was presented in figure 8;

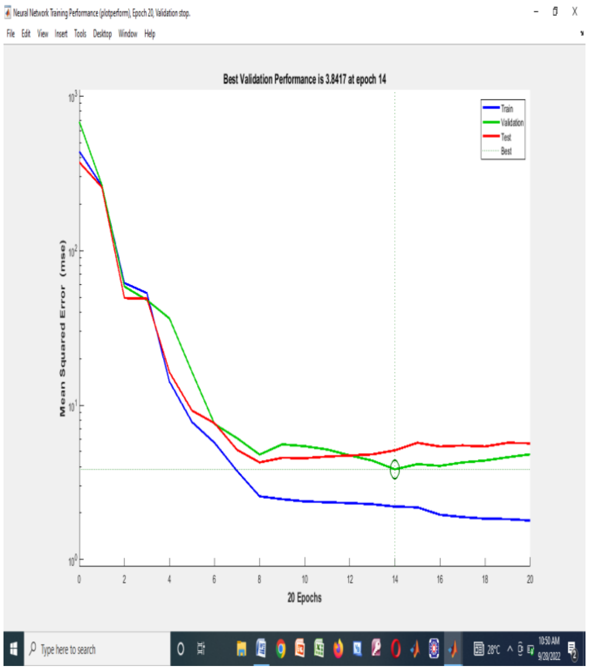

Figure 8: MSE performance of the neuro-algorithm

The figure 8 presented the performance of the neuro algorithm which was used or the optimization of the PLC. The result here was used to check the error which occurred during the training process, with aim of achieve error value approximately or equal to zero. The MSE achieved is 3.8417e-10 which is approximately zero which implied that the neurons learn the data of the tank perfectly. To test the ability of the neurons to detect nonlinearity on the tank, the regression was used which is a tool to evaluate the ability of neuron to solve fitting problem. The result of the R was aimed at achieve value approximately or equal to one. The result of the R was presented in figure 9;

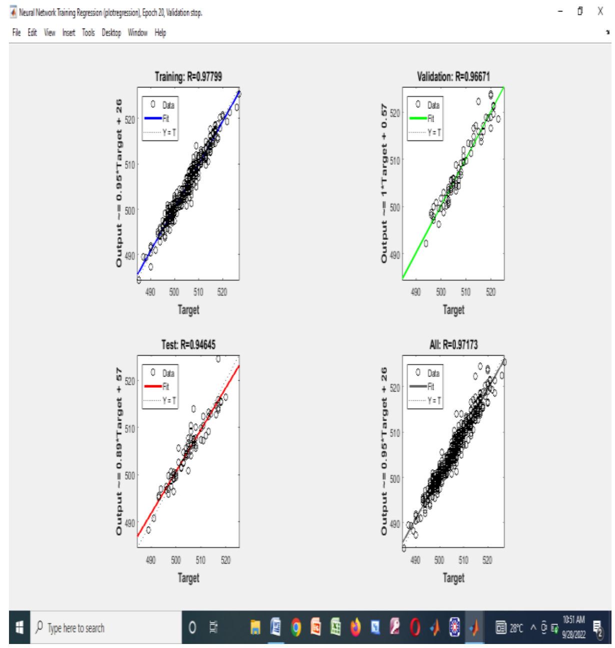

Figure 9: Regression result of the Neuro-algorithm

The figure 9 presented the regression performance of the Neuro-algorithm developed and used for the detection of imbalance slurry fluid rate in the tank. The result showed that the overall regression is 0.97173. The implication of the result is that the neuro-algorithm was detect when the fluid is + 3% (200 litres) and then control using the PLC.

Having developed the algorithm and integrated on the PLC via Simulink, the step response of the Neuro-PLC was presented in the figure 10;

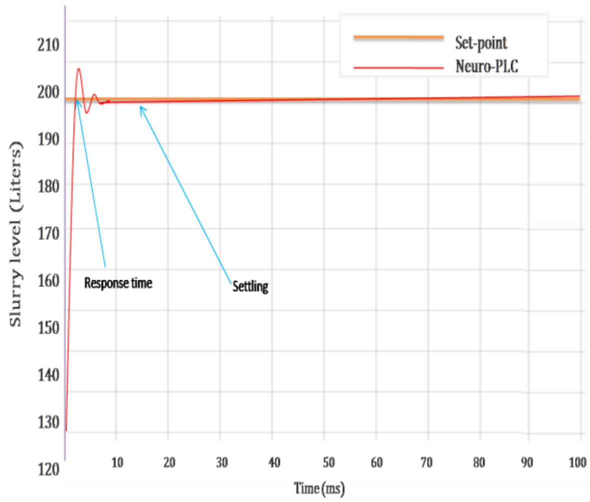

Figure 10: The step response of the Neuro-PLC

The figure 10 presented the step response of the Neuro-PLC when simulated on the plant to study the response to nonlinearity and maintain stability on the tank. The result showed that the rise time to rise time is instantaneous while the response time is 4.12ms, over shoot of 1.81% was recorded while the settling time is 9.17ms. The dead time is 13.29ms which is against the 55ms in the characterized PLC. The percentage improvement achieved in the step response is 77.65%.

6. CONCLUSION

This paper presented the improving the modeling of basic process control system for ceiling production using machine learning technique. The study identified the delay response o the PLC has contribute the many control challenges encountered during industrial automation. Neural network and data collected from Emenite was sued to develop an optimization algorithm and used to improve the performance of PLC. The result when evaluated showed that the Neuro-PLC achieved better control performance with an overall step response time of 13.29ms as against the PLC which is 55ms, thus giving a percentage improvement of 77.69%. The performance of the Neuro-PLC when integrated on the technical process for the production of slurry showed that the error was reduced and maintained at the desired tolerance limit based on the user requirements.

7. AUTHORS DECLARATION

The authors declare no conflict of interest in this manuscript.

8. AUTHORS CONTRIBUTION

All authors contributed in the development of this research, and collectively agreed it should be published.

9. FUNDING

None

10. DATA AVAILABILITY

Dataset used for the neural network training was available at the Emenite Nigeria Limited, Enugu, Nigeria.

11. ACKNOWLEDGEMENT

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12. REFERENCES

Anthony E., (2018) "Reconsidering the industrial revolution: England and Wales". Journal of interdisciplinary History 49.01: pp 9-42.

Eneh J., and Ene P., (2020) "Optimizing the control and automation of variable torque on 3phase induction motor using programmable neuro logic controller and VFD"; NIJOTEHC; Vol 39; no 3; pp. 887-895.

Inyama H., and Agbaraji C., (2015) "A Survey of Controller Design Methods For A Robot Manipulator In Harsh Environments"European Journal of Engineering and Technology; Vol. 3 No. 3, 2015;ISSN 2056-5860

Mallikarjun G., Umayal R., Shiva K., Raghavendra H., (2017) "Programmable Logic Controller (PLC) in Automation", Advanced Journal of Graduate Research ISSN:2456-7108 Volume 2, Issue 1, pp. 37-45, July 2017

Mba J., and Asogwa T., (2022) "Modeling of neuro-based strategy for mitigating cyber threat in 4G wireless network using artificial intelligence technique" (J) IJAICCSS; vol 1; issue 7; pp. 2-16.

Parrish J.,Brosilow C., (2016)"Nonlinear Inferential Control of Reactor Effluent Concentration from Temperature and Flow Measurements". In Proceedings of the 2016American Control Conference, Seattle, WA,pp 1027-1033

Rahul U., and Rajesh S., (2010) "Analysis of CSTR Temperature Control with Adaptive and PID Controller (A Comparative Study)", IACSIT International Journal of Engineering and Technology, Vol.2, No.5, October 2010; ISSN: 1793-8236

Smith (2017), "Process Control for the Process Industries - Part 2: Steady State Characteristics". Chemical Engineering Progress: 67–73.

Tan W., Marquez H., Chen T. and Liu J., (2015), "Analysis and control of a nonlinear boiler-turbine unit", Journal of process control, vol. 15, pp. 883-891, 2015.

Telegam S., (2016), "Improving steady state simulation results of a continuous stirred tank reactor (CSTR) system using Aspen-plus simulation", Department of Chemical Engineering NIT Rourkela 769008